

Development of an Immunity-based Framework for Power Plant Monitoring and Control

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Abstract

In this paper, the artificial immune system paradigm is used to formulate a comprehensive and integrated framework for monitoring and control of advanced power plants. The proposed data-driven methodology is envisioned to address directly the complexity and multi-dimensionality of modern power plants and support their safe operation at desirable levels of performance under normal and abnormal conditions. Abnormal condition detection, identification, evaluation, and accommodation are addressed. A preliminary numerical simulation example using an integrated gasification combined cycle power plant illustrates the general concept and the proposed computational tools.

Keywords

Artificial Immune System; Power Plant Monitoring and Control; Abnormal Condition Detection

Introduction

Modern power plants are highly complex and multi-dimensional. These plants need to be operated at their maximum efficiency in the face of disturbances and/or abnormal conditions without violating environmental emission standards and causing safety hazards. Handling this challenging task requires intelligent monitoring, decision making, and control. The artificial immune system (AIS) paradigm has the capabilities to provide a comprehensive and integrated solution to such a challenging task.

The functionality of the biological immune system and its response to intruding pathogens inspired the AIS paradigm as a novel artificial intelligence technique which was successfully applied over the past decade to a wide range of real-world problems including, but not limited to fault detection, pattern recognition, control and robotics, computer viruses detection, machine learning and classification [1].

Effective condition monitoring in power plants requires that all abnormal conditions be identified through comparisons with normal or baseline conditions [2]. However, it is not possible for each and every component of a complex power generation train to be identified in such a manner [2]. In addition, strong interactions among the variables make it difficult to identify the normal conditions as the power plant follows the load. Therefore, a comprehensive and integrated approach is required that can provide an efficient condition monitoring framework [3]. Such a framework is proposed in this paper based on the AIS paradigm, which is expected to be capable of handling the complexity and multidimensionality of the problem.

Problem Formulation and Nomenclature

Let the *targeted system* or simply *system* be composed of a number N_s of subsystems, possibly nested, such that each subsystem i may be composed of N_{ci} sub-subsystems or components. Consider the *targeted system* to be a power plant with all equipment items, including hardware used for measurement and control such as actuators, sensors, automation devices, and others. Human operators and the environment may also be considered part of the targeted system. In general, within a subsystem, a component may interact both ways (input/output) with one or

more other components creating internal loops. Similarly, subsystems may interact with one or more other subsystems. This structure is illustrated in FIGURE1.

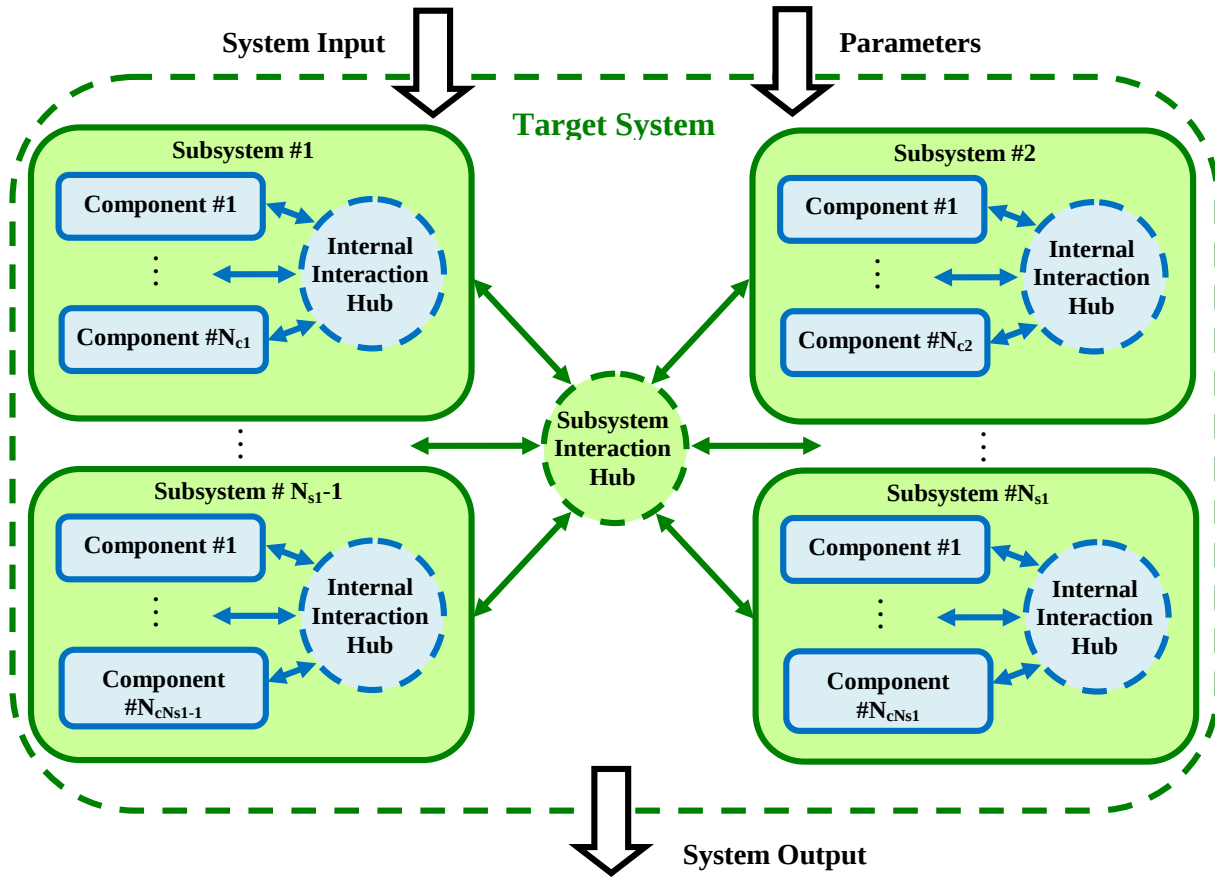


FIGURE 1. GENERAL TARGETED SYSTEM AND ITS COMPONENTS

Let the *system input* or *control variables* be those variables that can be dynamically varied by the user for control purposes. Let the *system parameters* be those characteristics of the system that are considered constant during system operation. Some of them may be setup or selected by the user. Let the *output* consist of variables produced by the system (controlled variables and others). These variables may be used in the calculation of the optimization criteria, for control and/or monitoring purposes. Relevant internal system variables will be referred to as *states* disregarding whether or not they form a minimal set. Control variables, parameters, states, and outputs may be affected by disturbances whose magnitudes may be within normal operation boundaries or not. Note that the structure subsystem/component may be extended over additional levels. Note also that the internal interaction between the components and the interactions between subsystems are graphically represented in FIGURE 1 as generic interaction hubs.

The generic term “*abnormal conditions*” (AC) refers to situations that are outside the general design framework and require specific attention and/or action for system performance and safety purposes, such as faults and failures of hardware, exceedance of nominal operational ranges, human operator-related abnormal situations, operational upset conditions, and extreme environmental conditions. It should be noted that for the practical design and implementation of comprehensive AC detection, identification, evaluation, and accommodation (ACDIEA) schemes, the designer is required to identify the nature, type, and severity of the AC targeted.

The *detection* represents the process through which the existence of an AC is assessed or, in other words, a failure within at least one of the targeted system components (or subsystems) has been acknowledged. The outcome of the detection process is binary.

The *identification or isolation* process determines which subsystem has failed. Depending on the complexity of the targeted system, the AC identification can be performed in several phases. For example, a first identification phase could determine that a certain subsystem such as an absorber or turbine has been affected by the AC. A second

phase could determine which specific component has failed, such as a valve or a pressure sensor. The outcome of the identification process can be formulated as an N_s -dimensional vector with binary components or as a set of integers labeling only the failed subsystems.

Once a failure has been detected and correctly identified, the AC *evaluation* process must address three aspects. One is of a qualitative nature and involves determining the type of the failure. For example, a faulty valve may cause a very high pressure drop or it may leak when completely shut off. The other two aspects are of a quantitative nature and can be defined as direct and indirect. The direct failure evaluation consists of estimating the magnitude or severity of the failure (e.g., the amount of fluid loss due to leakage). The indirect failure evaluation includes the re-assessment of system operation and prediction of the limitations and constraints on the performance and safety inflicted by the presence of the failure.

The outcome of the qualitative evaluation is an N_{sf} -dimensional string of integers labeling the type of failures for all N_{sf} affected subsystems out of a list of N_{ft_k} , $k = 1, 2, \dots, N_s$, potential types associated to each failed subsystem.

The outcome of the direct quantitative evaluation process can take a numerical value that relates to the magnitude or severity of the AC. For example: an outcome of 40% may represent, let's say, the relative reduction of flow rate due to a faulty valve obstruction. While possible in some cases, this level of accuracy may be difficult to achieve in general. Alternatively, the direct quantitative evaluation could provide a severity estimate mapped on a discrete set (e.g. low severity, medium severity, and high severity) or it could provide a severity evaluation based on fuzzy logic and expressed as fuzzy membership values with respect to the linguistic values associated to the discrete set of severity metrics.

The outcome of the indirect quantitative evaluation process typically represents a set of new ranges at post failure conditions of the variables that define the system operational envelope, in its most general meaning.

The *accommodation* process can take two forms: *passive accommodation* through warnings and other information provided to the supervising personnel and *active accommodation* through direct compensation as integral part of the system control laws. The passive accommodation represents actually the re-processing of the outcomes of the detection, identification, and evaluation and their delivery to the supervising personnel in a form that is easy to perceive and understand. The direct accommodation may consist of re-evaluation of system parameter (optimization under new conditions) and/or triggering of pre-existing compensating modules within the control laws and/or actual computation of commands at post-failure conditions.

Biological Immune System and the Artificial Immune System Paradigm

The biological immune system consists of two main components: the innate and the adaptive system [4]. The innate immune system relies on specialized cells, such as dendritic cells (DC), which respond immediately to any class of pathogen as a first line of defense. These cells are generated through a negative selection process which allows them to bind to biochemical markers that are specific to the antigen (non-self) and not to the own organism (self), as illustrated in FIGURE 2.

DCs are capable of detecting antigens and assessing the level of antigen invasion vs. defense response as a balance between "danger" and "safety". This information is transferred to lymph nodes regulating the generation of lymphocytes (T-cells and B-cells) as a main component of the immune adaptive system. T-cells are composed of assistant or helper Th-cells and suppressing Ts-cells, which stimulate and suppress, respectively, the proliferation of B-cells and, as a consequence, of antibodies. If the level of danger is high, more helper Th-cells are produced, which results in more B-cells being generated. If the number of antigens is reduced, the number of Ts-cells increases and the number of B-cells reduces accordingly. Due to this immune feedback mechanism (see FIGURE3), the immune system has the tendency to reach a normal dynamic balance after a period of time with minimum use of resources. As a parallel process, to accelerate future responses to the same antigen, memory B-cells and T-cells are generated, which remain dormant until a new infection takes place.

An abnormal situation affecting a dynamic system, which can be considered similar to an invasion by external antigens, can be declared when the current configuration of "features" does not match with any configuration from a pre-determined set known to correspond to normal situations. These "features" – similar to the chemical

compounds that form the biological identifiers – represent the encoding of the self. The self is accessible through simply operating the system at normal conditions and measuring the features. Once the self and non-self are determined, status information can be further extracted using immunity mechanisms. The regulatory action associated with antibody generation can serve as inspiration for the development of optimization and control algorithms.

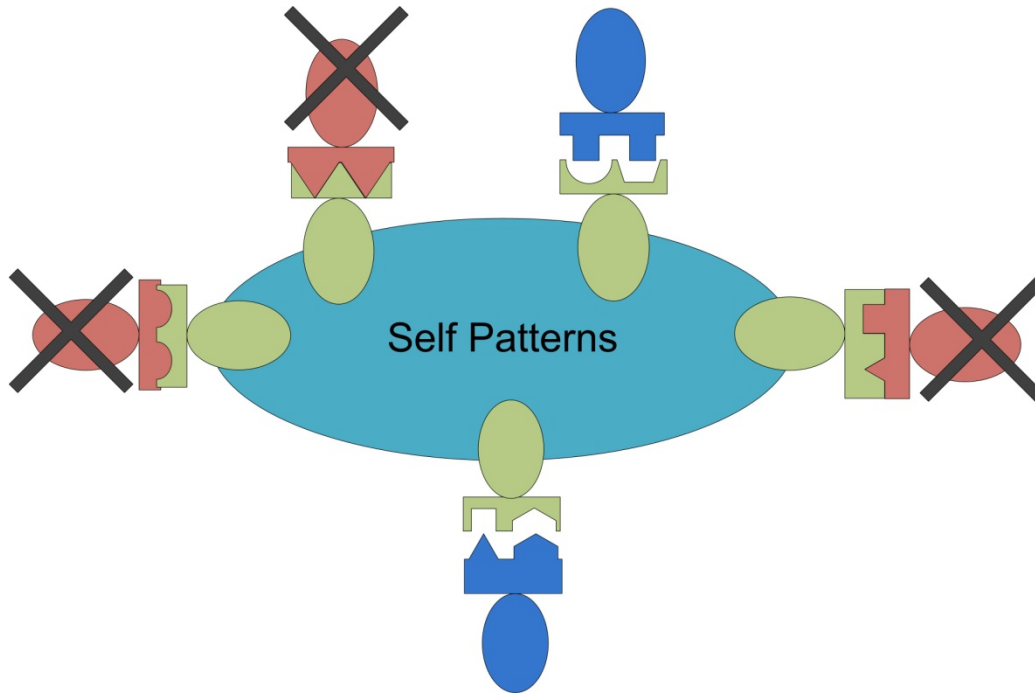


FIGURE 2. NEGATIVE SELECTION MECHANISM

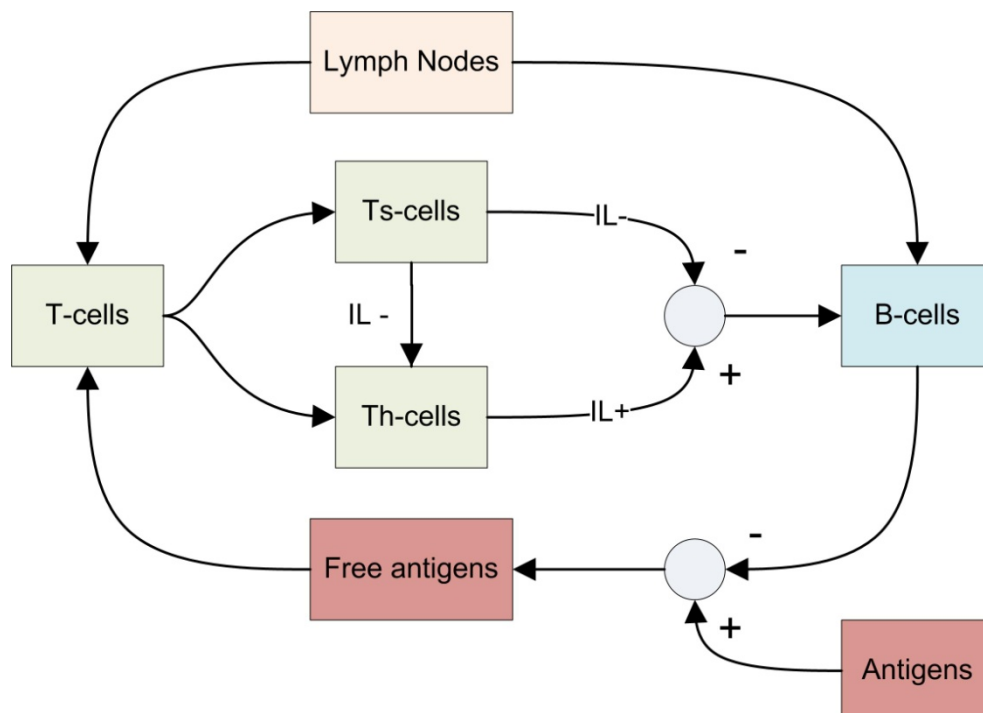


FIGURE 3. BLOCK DIAGRAM OF THE HUMORAL IMMUNE FEEDBACK RESPONSE

General Architecture of the Immunity-Based Framework

The biological immune system consists of two main components: the innate and the adaptive system [4]. The innate immune system relies on specialized cells, such as dendritic cells (DC), which respond immediately to any.

The power system monitoring and control process based on the AIS paradigm is considered to include three main components functionally connected in a closed loop (FIGURE 4):

- biomimetic monitoring and control (BMC) system design, implementation, and update
- on-line ACDIEA
- processing of system operational data and ACDIEA outcomes for off line/on-line system update

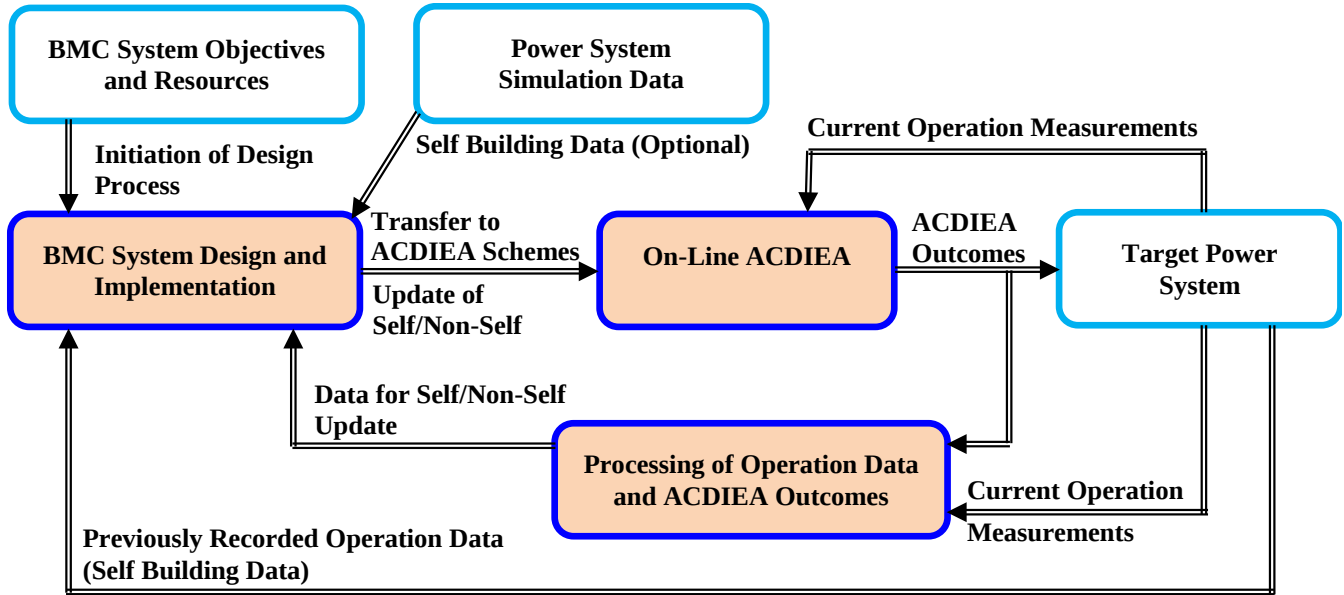


FIGURE 4. POWER SYSTEM BIOMIMETIC MONITORING AND CONTROL PROCESS

The *BMC system design, implementation, and update* have an off-line and an on-line component. The outcome of the off-line component consists of the initial development of an integrated and comprehensive ACDIEA scheme. This component in conjunction with the baseline controller mimics the innate immune system as a first line of defense against external intrusion. The design of the ACDIEA scheme depends on a clear definition of the targeted system subsystems and components that are targeted, including the types of AC (including known and unknown failures), the failure severity scale, the operational envelope variables, and the nature and level of passive and active accommodation. The development of the ACDIEA scheme requires the availability of large amounts of measured data that must be pre-processed for self/non-self generation and structuring. The on-line component is expected to provide extension and update of the BMC system based on current operation. In conjunction with the adaptive control component, it mimics the actions of the adaptive immune system.

The *on-line ACDIEA* process implies the real time operation of the ACDIEA scheme. Sets of current values of the features measured during current system operation at a certain sampling rate are compared against the detectors, identifiers, evaluators, and compensators and the outcomes of the ACDIEA are generated. These outcomes are transferred to the supervising/operating personnel, the automatic monitoring and recording system, and the automatic fault tolerant control laws.

The *processing of operation data and ACDIEA outcomes* consists primarily of analyzing the false alarms and failed detections in conjunction with current measured values of the features for modifying/extending the self/non-self and improving the overall performance for future operation. This process is also envisioned to re-assess the operational conditions, re-optimize parameters, and/or trigger switching between different operational modes.

The power system BMC process can be accomplished through the development and implementation of four major components as illustrated in FIGURE 5:

- Evolutionary Optimization Module (on-line/off-line)
- AIS for System Status Monitoring
- AIS-based Abnormal Condition Detection, Identification, and Evaluation Schemes

- Control System: Baseline + Adaptive Component

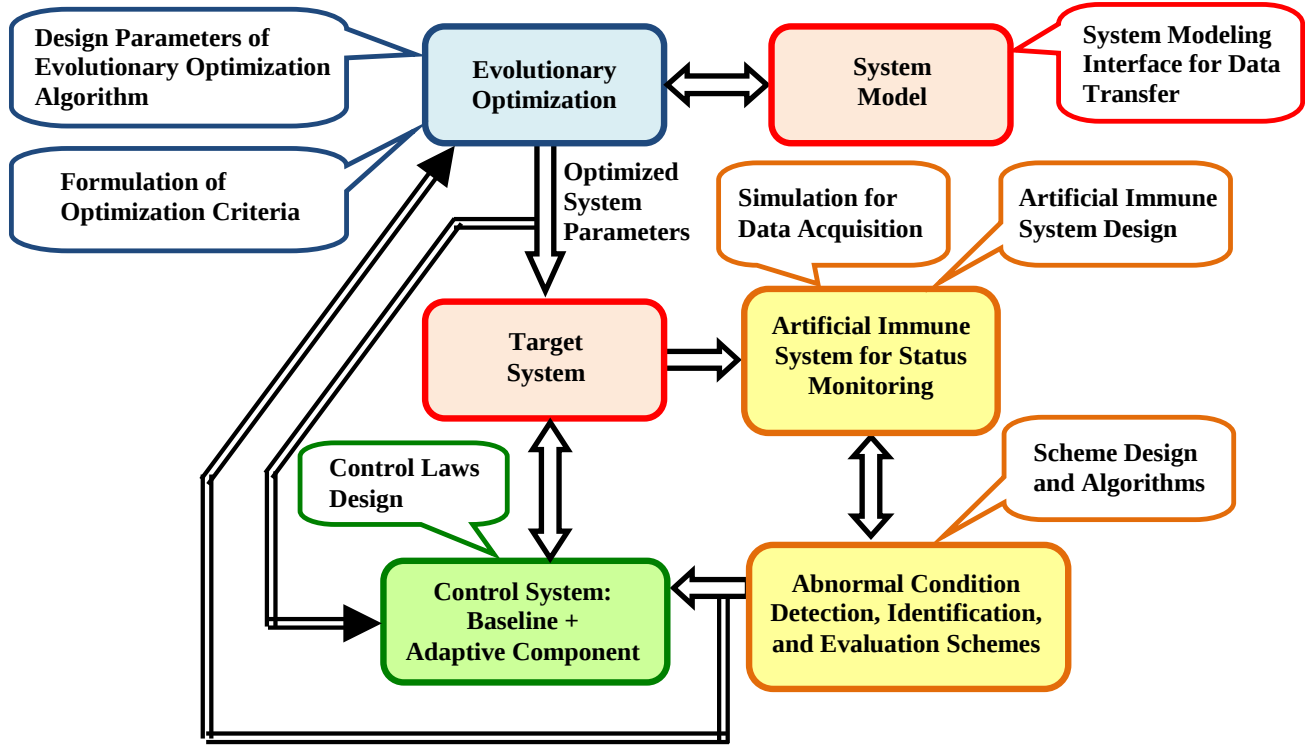


FIGURE 5. GENERAL FRAMEWORK ARCHITECTURE

Framework Components and Implementation

AIS Definitions and Concepts

The *feature variables* or shortly *features* are the variables φ_i that completely define the targeted system and are expected to capture the fingerprints of all AC considered, in terms of occurrence, presence, and severity. They can be (sub)system states, inputs, control system variables, parameters, estimated values, etc. The set of all features $\mathfrak{F}$:

$$\mathfrak{F} = \{\varphi_i \mid i = 1, 2, \dots, N\} \quad (1)$$

defines a *feature point* P as a set of simultaneous values of all features φ_i that can be obtained through measurements or simulation, at normal or abnormal conditions. The set $\mathfrak{F}$ defines an N -dimensional hyper-space U , which will be referred to as the “Universe”. An orthogonal coordinate system (CS) equally denoted U is associated to this hyper-space. Its origin is at point O with coordinates $[\varphi_1 = 0 \ \varphi_2 = 0 \ \dots \ \varphi_N = 0]$. Therefore, the feature point P can be represented by the position vector with respect to O , $\vec{r}^{OP}$, whose coordinates with respect to CS U are denoted as:

$$[\vec{r}^{OP}]_U = S[\varphi_{1P} \ \varphi_{2P} \ \dots \ \varphi_{NP}]_U^T \quad (2)$$

The self S is defined as the hyper-sub-space of all possible feature points at normal conditions. All other points in U form the non-self $\hat{S}$. Therefore:

$$S \cup \hat{S} = U \text{ and } S \cap \hat{S} = \emptyset \quad (3)$$

For computational tractability and practical reasons, the self points are clustered. These *self clusters* can be shaped as hyper-spheres, hyper-rectangles, or hyper-ellipsoids. Clustering of the non-self generates what is referred to as *detectors*. They may be directly used in the detection process. Structuring the non-self by adding information to the detectors makes them capable to be used in the failure identification process. Such upgraded detectors will be referred to as *identifiers*. Clusters of the self or non-self that are processed to be used for evaluation or accommodation will be referred to as *evaluators* and *compensators*, respectively.

The threshold between “normal” and “abnormal” (i.e. between self and non-self) is represented by an N -dimensional surface:

$$\Sigma(\varphi_1, \varphi_2, \dots, \varphi_N) = 0 \quad (4)$$

Lower dimensional projections of the self will be referred to as *sub-selves*. Let us assume that we consider a 2-dimensional projection (or sub-self) defined by features φ_1 and φ_2 and we collect all possible feature points at normal conditions. Area 0 will result in that as shown in FIGURE 6. Note that typically normalized values are used for the features; therefore, a working sub-region of the universe U is used next, which is represented as a hyper-cube of side 1. The projection of Σ is represented as straight line segments for convenience, without loss of generality.

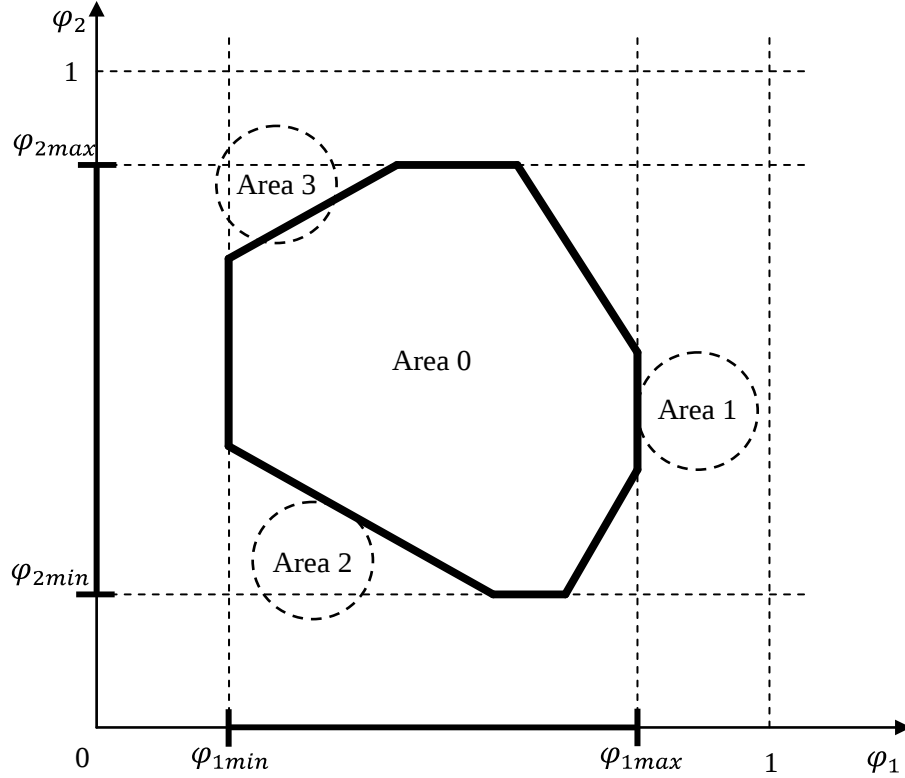


FIGURE 6. SELF/NON-SELF 2-DIMENSIONAL PROJECTION

All points outside Area 0 belong to the non-self $\hat{S}$. That means that whenever a pair of values (φ_1, φ_2) is measured that lies outside Area 0, a failure can be declared. However, whenever a pair of values (φ_1, φ_2) is measured that lies inside Area 0, it cannot be necessarily concluded that the conditions are normal. AC whose dynamic fingerprints depend on one or more other features can produce projections inside Area 0. The *order* of an AC, denoted as $Ord(AC)$, is defined as the minimum number of features necessary to completely detect that AC. A *complete detection* is said to be possible if all feature points produced at AC fall within the non-self. For example, a first order failure would require only one feature φ^* for detection. In other words, the presence of the failure necessarily produces always values of φ^* that are outside a normal range. In FIGURE 6, if Area 1 is the projection of all points under a certain failure, then that failure is first order with $\varphi^* = \varphi_1$. Similarly, Area 2 represents an AC of degree 2, and Area 3 a failure of degree 3 or higher. A complete detection of the failure represented by Area 1 can be performed using the 2-dimensional self defined by φ_1 and φ_2 , but also using only the projection, or the 1-dimensional sub-self defined by φ_1 . The 2-dimensional self is necessary and sufficient to completely detect the failure represented by Area 2. Using the sub-self defined by φ_1 will never succeed detecting this failure, while using the sub-self defined by φ_2 will allow detection in some instances, but not a complete detection. Using the 2-dimensional self to detect the third failure will not ensure a complete detection. However, it should be noted that,

in practice, the approach could achieve very high rates of detection if the feature points that are projected inside the self are reached with very low probability.

Generation of Self/Non-self

The central part of the proposed BMC system is the self/non-self and the most critical element of their generation is the selection of features. They must be relevant to all four processes (ACDIEA). Their number and nature depend on the subsystems and components that are targeted, including the types of AC, the failure severity scale, the operational envelope variables, and the nature and level of passive and active accommodation. For a comprehensive and integrated approach, all states, inputs, and variable parameters of all subsystems considered must be taken into account. It should also be noted that a complete detection of an N -degree failure requires N relevant features, therefore, an N -dimensional self. If the number of subsystems considered is N_s , then the states X_i , inputs U_i , and other relevant parameters P_i corresponding to subsystem i , $i = 1, 2, \dots, N_s$, can be expressed as, respectively:

$$X_i = [x_{i1} \quad x_{i2} \quad \dots \quad x_{iN_{si}}]^T \quad (5)$$

$$U_i = [u_{i1} \quad u_{i2} \quad \dots \quad u_{iN_{ui}}]^T \quad (6)$$

$$P_i = [p_{i1} \quad p_{i2} \quad \dots \quad p_{iN_{pi}}]^T \quad (7)$$

The order of an AC is defined as the minimum number of features that allow its complete detection. For any subsystem i , the maximum order an AC can have is:

$$N_i = N_{si} + N_{ui} + N_{pi} \quad (8)$$

Therefore, for a complete detection of all AC from an exhaustive set F , the number of necessary features to build the self/non-self is:

$$N = \sum_{i=1}^{N_s} (N_{si}^* + N_{ui}^* + N_{pi}^*) \quad (9)$$

where the *-variables exclude duplication among the sub-systems. If all states, inputs, and parameters are distinct, then:

$$N_{si}^* = N_{si}, N_{ui}^* = N_{ui}, \text{ and } N_{pi}^* = N_{pi} \quad (10)$$

otherwise, for example:

$$N_{si}^* = \begin{cases} N_{s1} & \text{for } i = 1 \\ N_{si} - n & \text{for } i > 1 \end{cases} \quad (11)$$

where n is the number of duplicate states for each subsystem, that is the states with the property that $x_{ij} \in X_i$ and $x_{ij} \in X_{i-1}$. It can be easily noticed that the number of necessary features N and hence the dimensionality of the self/non-self can become excessively large and create significant computational problems. These problems can be avoided under certain conditions by using lower dimensional sub-selves, or projections, within a hierarchical multi-self (HMS) strategy [5], [6].

Let the maximum order of failures in the set F be denoted as:

$$N_{max} = \max_j (\text{Ord}(f_j)), \quad j = 1, 2, \dots, N_F \quad (12)$$

$$\text{And } \text{Ord}(f_m) = N_{max} \quad (13)$$

If $N_{max} = N$, then a complete detection for f_m can only be obtained, in general, with an N -dimensional self. If the self/non-self has particular shapes, then at least on one of the $(N-1)$ -dimensional projections, the projection of the feature points at AC will fall inside the non-self. If $N_{max} < N$, then a complete detection for f_m can be obtained by

using an N_{max} -dimensional sub-self with proper features. In this situation, the N -dimensional self does not need to be considered. A complete detection for all failures can be obtained by using all possible N_{max} -dimensional projections or sub-selves. The approach is conservative and some of the projections may be ignored or replaced by lower dimensional projections without loss of performance. Determining the order of an AC may be difficult in many cases or even impossible; therefore, N_{max} may be unknown. In this situation, a low value for N_{max} may be assumed and the self/non-self can be built as the set of all possible N_{max} -dimensional sub-selves, with the observation that the higher the assumed value of N_{max} is, the higher the likelihood of better performance will be.

The generation of the self/non-self requires large amounts of measured data at normal conditions, ideally covering the entire operational envelope. These N -dimensional feature points are clustered and the self S is represented as a set of hyper-bodies including these clusters, which will be referred to as *self-clusters*. Similar hyper-bodies are used to represent the non-self as well and will be referred to as *detectors*. The geometry of these hyper-bodies can potentially have an impact on the efficiency of the detector generation process and on the detection itself [6]. The block diagram of the self/non-self generation process is presented in FIGURE 7.

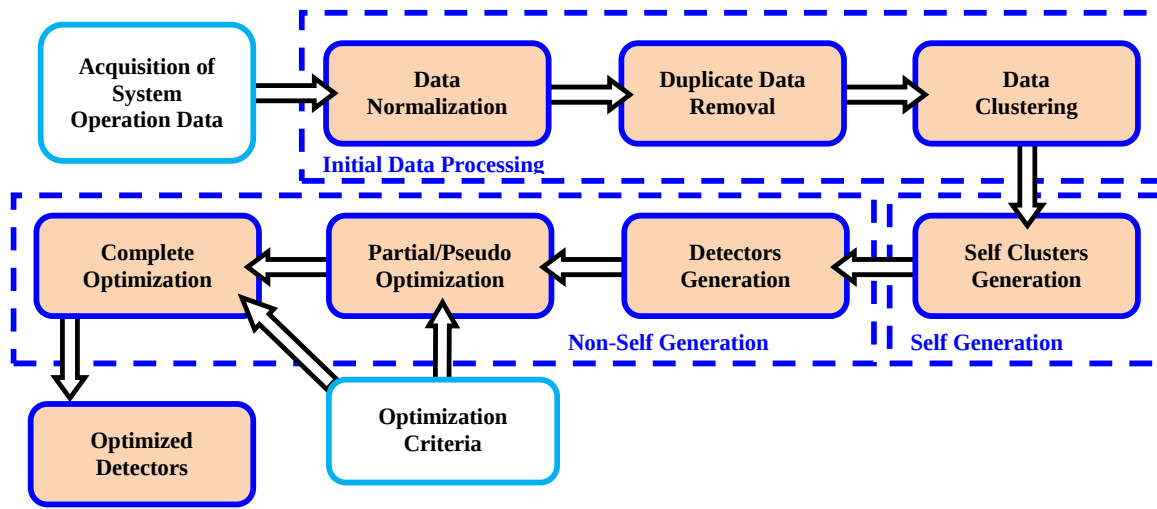


FIGURE 7. SELF/NON-SELF GENERATION PROCESS

To support the AC identification and evaluation processes, structuring of the non-self may be necessary to provide information regarding the sub-system affected, the type of the failure, and the failure severity. This can be achieved by attaching to each detector d_j a set of structuring tags dS_j :

$$dS_j = \{dSys_j \quad dFt_j \quad dFs_j\} \quad (14)$$

where, in general, $dSys_j \in \{1 \ 2 \ \dots \ N_s\}$, $dFt_j \in \{1 \ 2 \ \dots \ N_F\}$, and dFs_j consists of a set of failure severity metrics associated to each failure type in dFt_j and $size(dSys_j) = size(dFt_j) = size(dFs_j)$. The implication here is that each sub-system may be affected by only one failure at a time. The case in which a combination of failures occurs can be handled within this framework by defining in the set F a distinct AC with such multiplicity characteristics. Alternatively, for each sub-system represented by $dSys_j$, the elements of dFt_j and dFs_j may be defined as sub-sets of size larger than 1. In this case, $size(dSys_j) < size(dFt_j) = size(dFs_j)$. The three sub-sets in Eqn. (14) will each have only one element in the ideal situation when the N features have been defined perfectly and completely, one N -dimensional self is used, and the size of the detectors provides perfect resolution. In other words, any given detector can be associated to only one sub-system, one failure type, and one level of failure severity. It should be noted that the structured non-self approach for AC identification and evaluation requires prior extensive information regarding the AC. Alternative approaches within the HMS strategy using dendritic cells (DC) mechanisms mitigate and, under certain conditions, eliminate this drawback [7].

Immunity-based Abnormal Condition Detection

Immunity-based AC detection relies on the simple self/non-self discrimination. Incoming measurements of features

are compared against self-clusters (positive selection-type of algorithms) or detectors (negative selection-type of algorithms) and depending on their relative location a normal or abnormal condition is declared. With positive selection-type algorithms, a normal condition can be declared faster as soon as a self-cluster is identified that includes the incoming measurement point. However, an AC may be declared with some delay since such an outcome requires testing all self-clusters. Negative selection-type algorithm are likely to detect an AC faster, but at normal conditions, all detectors must be tested.

Immunity-based Abnormal Condition Identification

Previous information regarding the migration of features within the non-self as a result of different AC can be used to structure the non-self for failed subsystem identification [6] as illustrated in FIGURE 8. Such information can be obtained from tests, simulation, or analysis. An alternative approach involves the use of artificial dendritic cells [7] that can capture distinct patterns in the way that select non-self projections are triggered as a result of the AC.

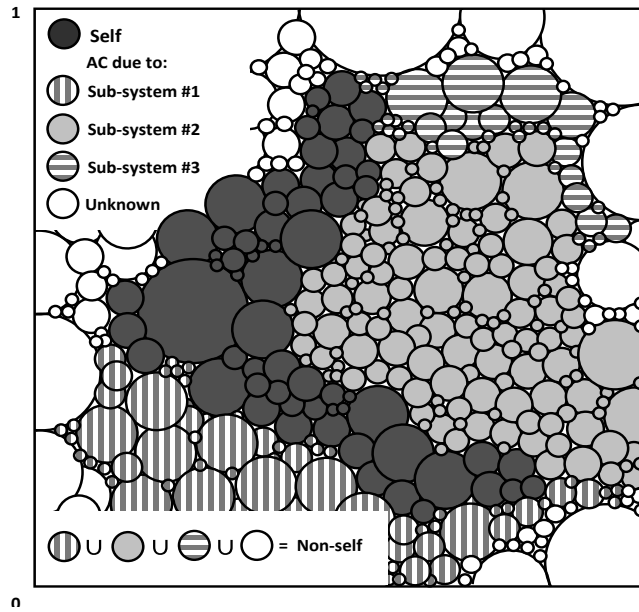


FIGURE 8. IDENTIFICATION OF FAILED SUBSYSTEM USING STRUCTURED NON-SELF

Immunity-based Abnormal Condition Evaluation

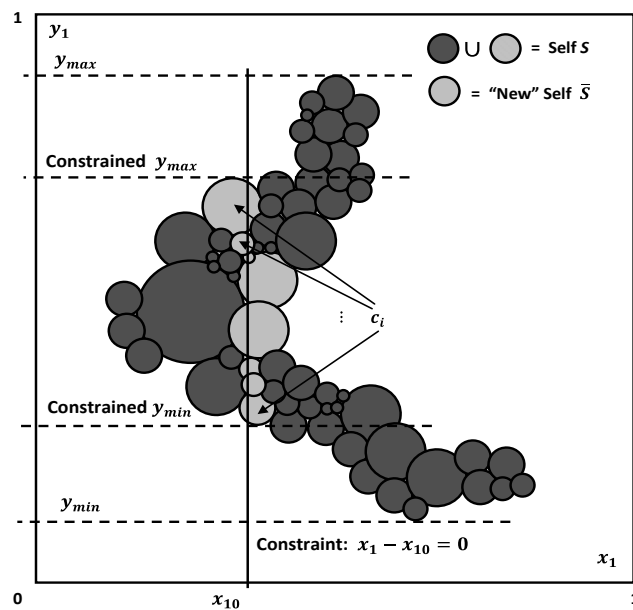


FIGURE 9. AIS-BASED POST-FAILURE OPERATIONAL ENVELOPE ESTIMATION

The qualitative evaluation and direct quantitative evaluation can be performed in a manner similar to the identification by using either the structured non-self approach or the artificial dendritic cells. The indirect quantitative evaluation requires specific customized algorithms depending on the subsystem, failure, and the affected parameter of the operational envelope. However, for classes of AC with certain characteristics, more general algorithms can be developed within the AIS paradigm. For instance, let us assume that the AC consists of constraints on a manipulated variable (x_1) that has a direct effect on a state or controlled variable (y_1), which in turn is relevant to the operational envelope and must be monitored. Both variables are part of the feature set. Let us also assume that the AC does not affect the nature of the relationship between x_1 and y_1 . Then the impact of the AC on the post-failure range of y_1 can be extracted from the 2-D self-projection on the (x_1, y_1) plane, as illustrated in FIGURE 9.

Immunity-based Abnormal Condition Accommodation

The immunity-based AC accommodation can be approached using two concepts. First, the humoral immune feedback response of FIGURE 3 that establishes a balance between the activation and suppression of the antibodies generation can be converted into an adaptive mechanism augmenting a baseline controller [3]. The second conceptual approach for using the AIS paradigm for control purposes relies on the assumption that the classification capabilities of the AIS can be extended [3] and used not only to detect the problem (AC) but also to select or find the solution, which is mitigating the AC effects. The control action is considered as a mapping between control variables and controlled variables under specific performance constraints.

Implementation Example

For demonstration purposes, an acid gas removal (AGR) unit [8] has been considered in this study. The unit is part of an integrated gasification combined cycle power plant [9]. Its objective is the removal of H_2S and CO_2 from the syngas using a physical solvent known as SELEXOL. The AGR unit contains more than 22 subunits with a total of 16 degrees of freedom. The first stage, in which most of H_2S is absorbed in the semi-lean solvent, is the H_2S absorber. The absorbed H_2S is then recovered in the H_2S stripper and concentrated in the H_2S concentrator before being sent to the Claus unit. The second stage, in which most of the CO_2 is captured, takes place in the CO_2 absorber. The captured CO_2 is then recovered by multi stage flash drums before reaching the CO_2 compression unit [8].

The process of defining the self involves two critical elements: establishing the definition of “normal conditions” and identifying the features capable to capture any departure from these conditions. The normal operation of the AGR unit involves operational, environments, and physical constraints. Table 1 shows the operational constraints within which the AGR unit is considered to be under normal conditions.

TABLE 1. AGR NORMAL CONDITIONS OPERATIONAL CONSTRAINTS

Constraint	Value
Percentage of H_2S captured	99.9% or higher of inlet H_2S
Percentage of CO_2 captured	91% or higher of inlet CO_2
Solvent temperature at the outlet of refrigeratorcoolers	4 °C
Solvent temperature at the outlet of water coolers	21 °C
Maximum compressor power	+20% of nominal
Maximum heat exchanger duty	+50% of nominal
Maximum allowable solvent temperature	175 °C
Maximum allowable water content of solvent	6%
Minimum Stripper pressure	276 kpa
Minimum Claus feed purity	30%

The AGR unit involves an extremely large number of variables; however, only a minimal set capable of capturing the distinction between normal and abnormal situations is selected as self/non-self defining feature set. The selection of the relevant features is based on process knowledge and expert assessment. A total of 171 relevant features have been identified for the AGR unit including pressure, temperature, flow rate, and fluid composition at different locations throughout the system. Ideally, a 171-dimensional self/non-self would solve the problem, but the computational burden is excessive. Within the hierarchical multi-self strategy, lower order projection may be

used instead. This number of features yield a total of 14,535 2-D projections; however, due to different levels of coupling between subsystems and their features, not all of those 2-D projections are necessary for abnormal conditions detection and/or identification. Grouping the features based on equipment or subsystem and removing those 2-D projections that involve subsystem features that do not interact, allows the reduction of the 2-D projections necessary for self/non-self definition down to 447 2-D projections or subselves.

The data collection process was performed using an AGR stand-alone model build within DYNsIM software package. It involved changing the set point of specific flow rates, temperatures, and pressures within predefined ranges. The collected data was then classified based on meeting the operational constraints to normal and abnormal. The normal data was then used to build the set of the 2-D projections (i.e. the self). Building each projection involved the following:

- 1- Normalization of each feature data between 0 and 1 based on the feature minimum and maximum values during the tests.
- 2- Clustering the data by means of hexagonal tessellation. It consists of grouping data points into circles to minimize the needed memory, while maintaining required accuracy of domain coverage.
- 3- Generating the detectors by means of negative selection-type algorithm through accurate coverage on the non-self domain.

The following figures are examples of a 2-D projection with test data that demonstrate the general implementation of the proposed approach and the capabilities of the AIS to detect system abnormal conditions. FIGURE10 presents the self clusters and non-self detectors with test data at normal conditions. All test points fall inside the self-clusters, as expected. Furthermore, Fig 11 presents data points from tests under abnormal conditions. These data points migrate into the non-self domain and fall inside detectors.

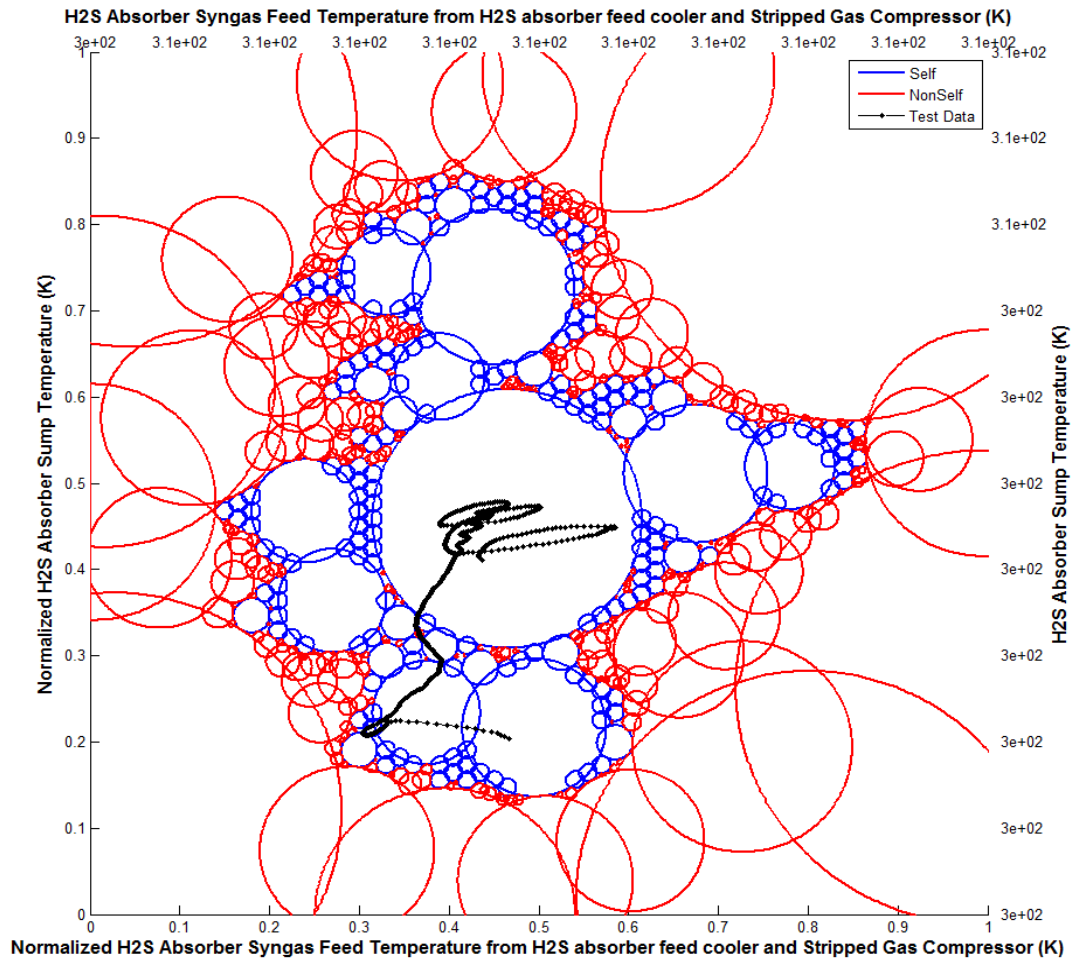


FIGURE 10. SELF/NON-SELF AND TEST DATA AT NORMAL CONDITIONS

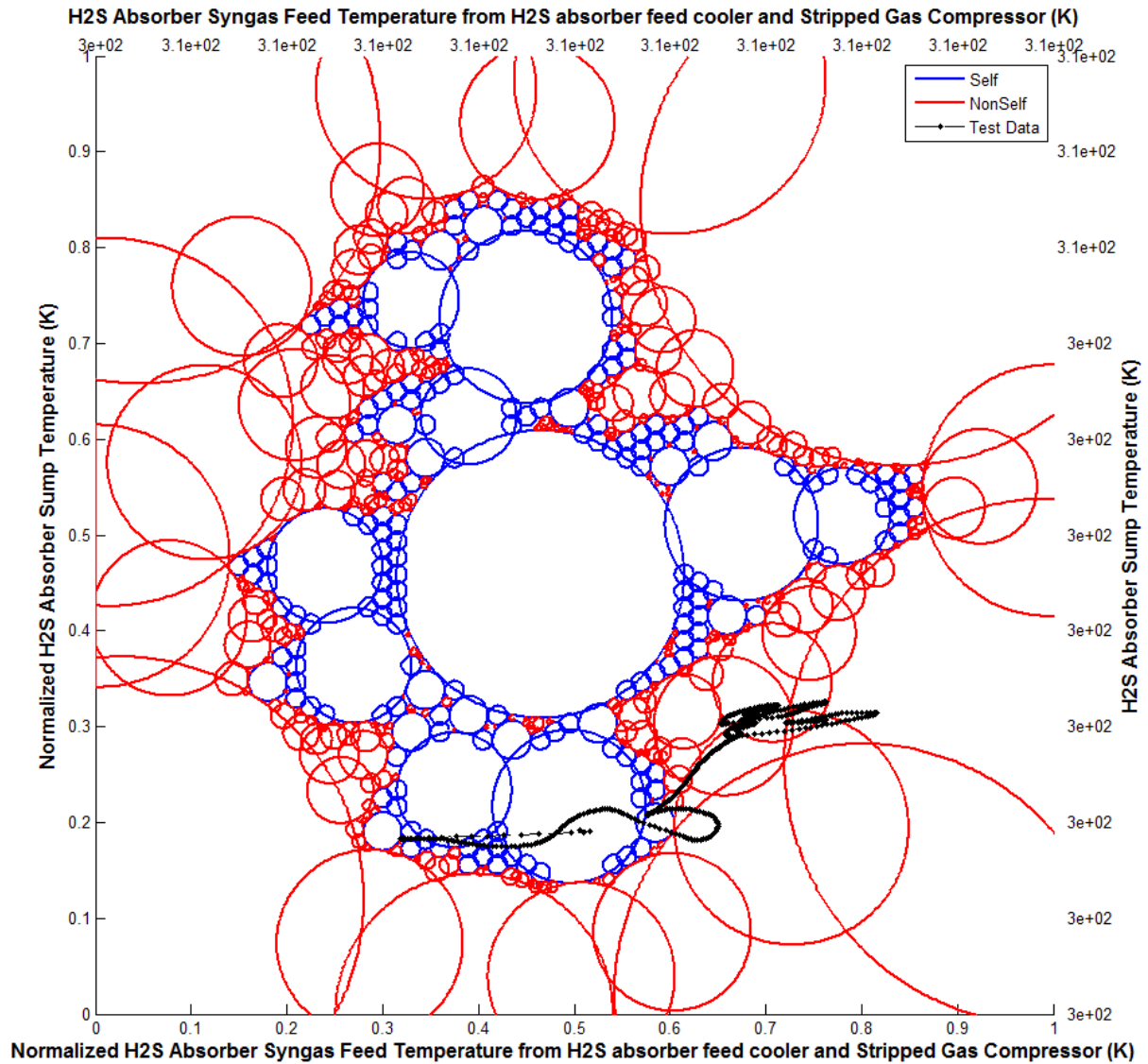


FIGURE 11. SELF/NON-SELF AND TEST DATA AT ABNORMAL CONDITIONS

Conclusions

The development of an integrated and comprehensive framework based on the AIS paradigm for the monitoring and control of complex plants is presented in this paper.

The capability of the AIS paradigm to address all relevant processes including abnormal condition detection, identification, evaluation, and accommodation is demonstrated through their integration within the algorithmic framework.

The proposed definition of the AIS self and non-self is successfully implemented for an AGR unit through numerical simulation.

Preliminary results demonstrate the capability of the AIS approach to discriminate between normal and abnormal conditions for the system considered. These results also show that the AIS paradigm in conjunction with the hierarchical multi-self strategy promises to be able to handle the complexity and multi-dimensionality of such systems.

ACKNOWLEDGMENT

This research effort is sponsored by US DOE - National Energy Technology Laboratory through grant DE-FE0012451.

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